Sandia National Laboratories

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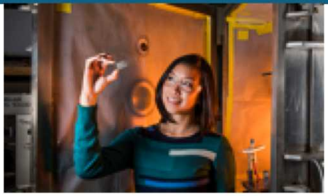
A causal perspective on reliability assessment



PRESENTED BY

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Background

Causality in an engineered system pertains to how a system output changes due to a controlled change in the system or system environment.

- Engineered systems designs reflect a causal theory regarding how a system will work
- Predicting reliability often requires knowledge of this underlying causal structure.

Formal causal inference methods have played a large role in many fields over the past decades, e.g. epidemiology and the social sciences.

- Recent interest in causality in AI fueled by Judea Pearl.

When do we need formal causal inference tools in engineering applications?

- Can tools like structural causal modeling inform with reliability estimation?

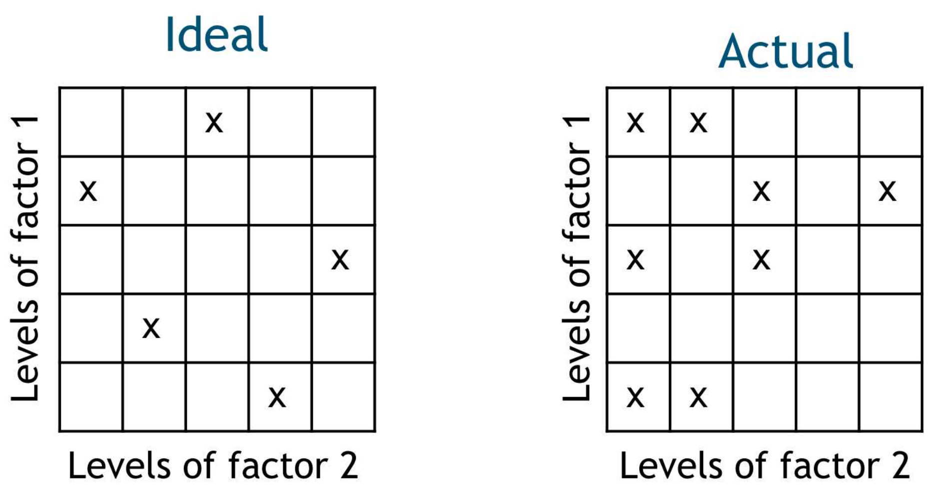
Background

When you want to know if X causes Y, what is the ideal study design?

- Randomization!
- Examples: clinical trials, design of experiments
- What happens when you don't have perfect data?

Causal inference methods pertain to **counterfactuals.**

- Used with observational data – what you see is what you get
- Hypothetical intervention in a population - P[Y|do(X=x)]



Causal inference in engineering applications

Limited work on causal inference methods in engineering applications.

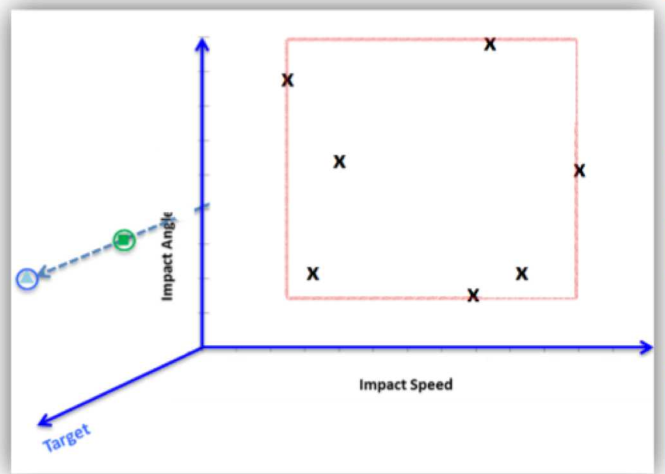
- Aven 2014; Broniatowski and Tucker (2017); Li & Shi 2007; Marazopoulou et al. 2016.

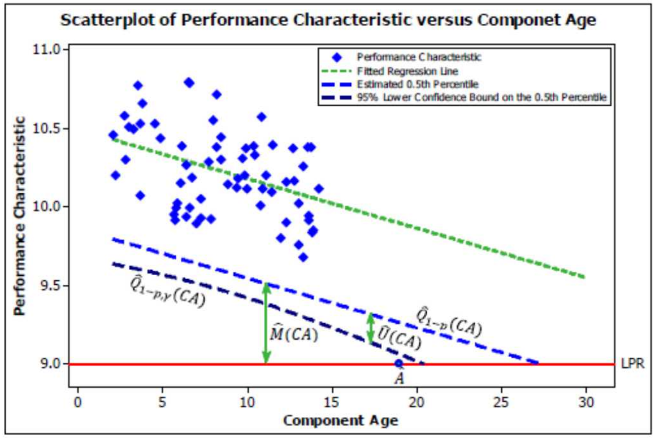
National defense problems are all about counterfactuals, i.e. "extrapolative prediction."

- System components: Predicting performance across various designs and environments with limited data.
- Computer models: Predict to setting without data.

Engineers are good at counterfactual prediction.

- Are there areas where formal causal inference might help?





Example: Addressing selection bias

Voltage of a thermal battery over time

- Batteries must meet a minimum voltage requirement (26.8V) throughout 25-year lifespan for different inputs and environments with 98% reliability.

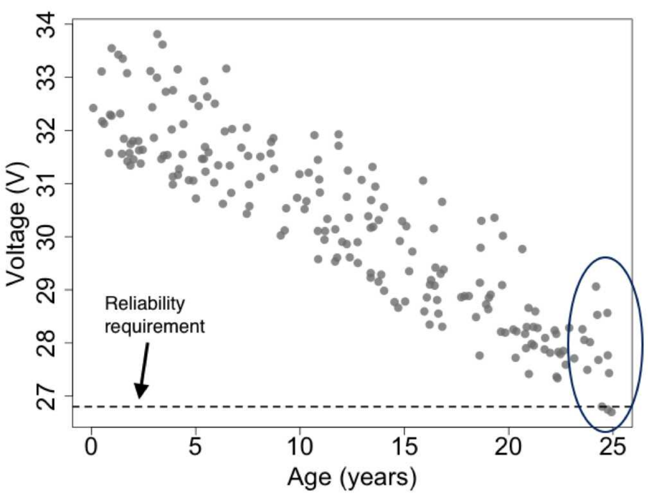
Data were collected on battery voltage over time (n=200 total tests).

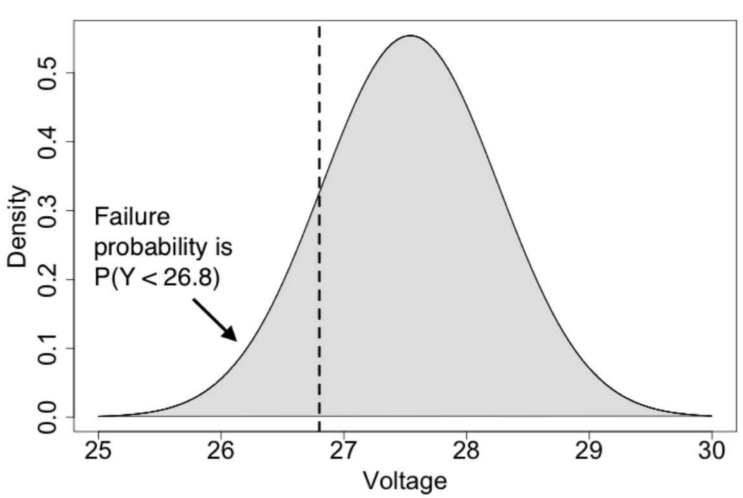
- Naïve analysis using linear model of voltage over time results in 85% reliability estimate.
- $Y|A = 25 \sim N(\beta_0 + \beta_1 * 25, \sigma^2)$

However, data contain biases:

- Load is higher, on average, than what would be expected in normal use conditions.
- Load is not recorded in the data.
- Actual quantity of interest: P(Y|do(A=a))

Data contain selection bias on a variable not measured in the data.





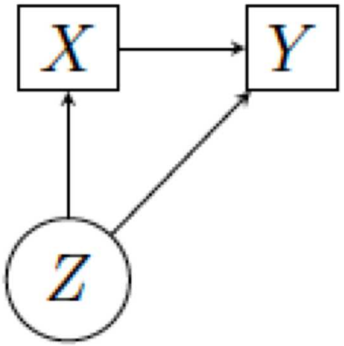
Structural causal modeling

We apply the structural causal modeling (SCM) framework (Pearl 2009; Pearl & Bareinboim 2016) to illustrate how causal modeling can be used in a reliability application with "imperfect" data.

- Common types of "imperfections:" selection bias and confounding bias.
- Goal: Ensure data analysis methods reflect the **data generating mechanism.**

Structural causal model specifies how model inputs (U) relate to model output (Y).

- SCM M = {F, U, Y}
- Full model is not known, but *existence* of causal relationships between observed and unobserved inputs and outputs is specified.



Graphical representation of a data generating mechanism and underlying causal structure.

Structural causal modeling

In practice, we want to move from ***qualitative*** DAG model to ***quantitative*** statistical model in order to estimate a causal query.

$$\begin{tikzcd} X \arrow[r] & Y \\ Z \arrow[u] \arrow[ur] & \end{tikzcd}$$

Example: Backdoor adjustment formula for confounding adjustment:

$$P\big(Y|do(X=x)\big) = \sum_z P(Y|X=x, Z=z)P(Z=z)$$

Unobserved counterfactual

Observed in data

Stratifying on Z, we can estimate the counterfactual of interest from the data.

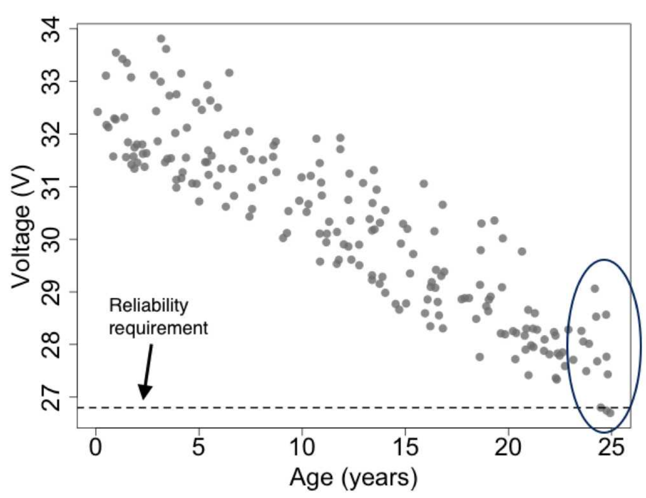
Types of statistical modeling assumptions

When applying the adjustment formula, there is a need to distinguish between 'structural' and 'functional' modeling assumptions.

- **Structural:** Have we collected a sufficient set of variables Z to estimate the causal query?

- **Functional:** Assuming we have collected the right data, is the model for the data sufficient (i.e., are $P(Y|X = x, Z = z)$ and $P(Z = z)$ correctly specified)?

$$P\big(Y|do(X = x)\big) = \sum_{z} P(Y|X = x, Z = z)P(Z = z)$$



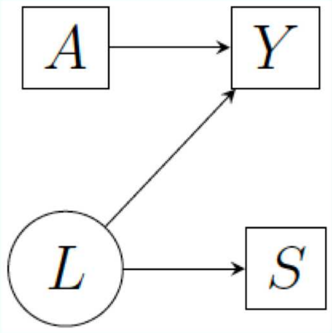
Steps of causal analysis

1. Define a causal query.
2. Determine how the collected data relates to the true underlying structural causal model.
   - Make a causal diagram.
3. Check if sufficient data to estimate query (structural assumptions).
   - Path between selection indicator and voltage through unmeasured load suggests not estimable.
4. Estimate the query from the data, collect more data, or do a sensitivity study (functional assumptions).

Step 1: Causal query

$$P\big(Y = do(A = a)\big)$$

Step2: DAG



Sensitivity study

Formula to estimate causal query under selection bias (Bareinboim & Pearl 2016):

$$P(Y|do(A=a)) \quad = \quad \int_l P(Y|A=a, L=l, S=1)\,\underbrace{P(L=l)}_{true\,dist.}\,dl$$

We can conduct sensitivity study by making assumptions about:

- The true load distribution: P(L=l)
- The relationship between voltage, load, and age: P(Y|A=a, L=l, S=1)
- The load distribution in the selection sample: P(L=l|S = 1)

Sensitivity study

Formula to estimate causal query under selection bias (Bareinboim & Pearl 2016):

$$P(Y|do(A=a)) = \int_l P(Y|A=a, L=l, S=1)\underbrace{P(L=l)}_{true\,dist.}\,dl$$

Specify statistical model:

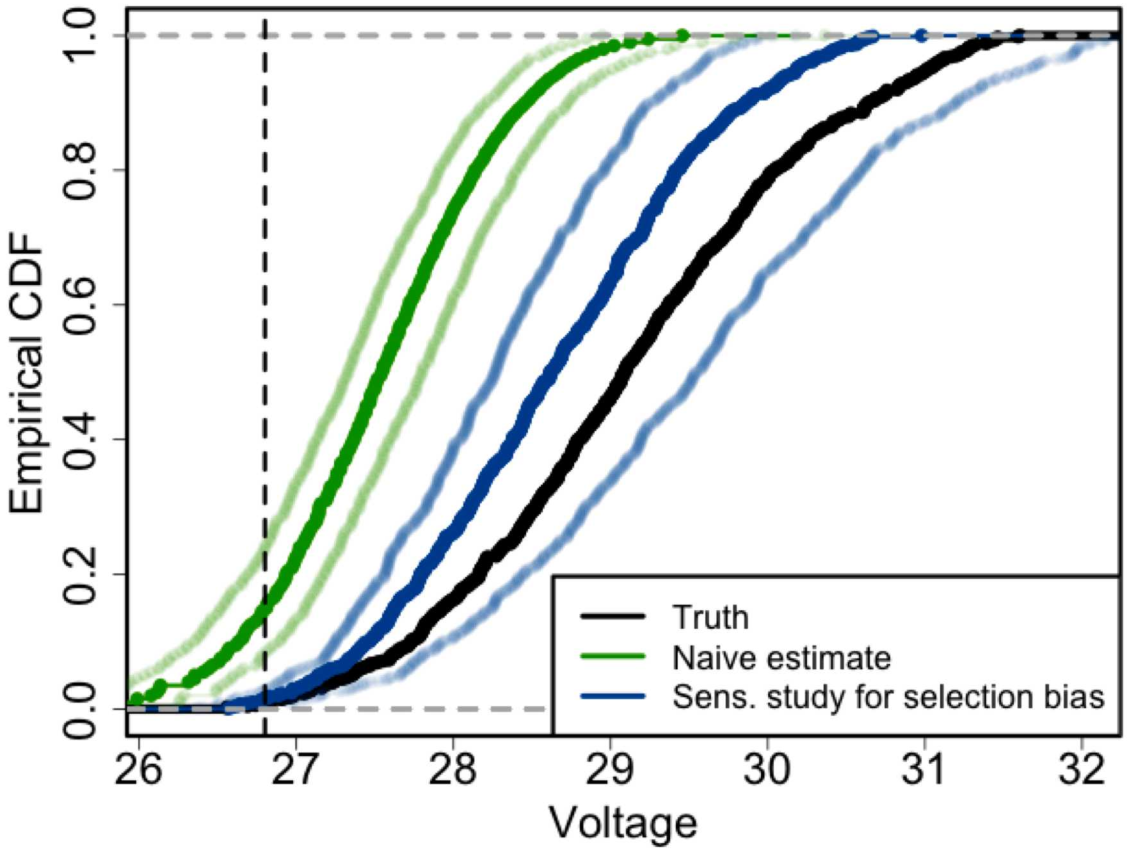
$$\begin{aligned}
Y_i|A_i, L_i, S=1 &= \beta_0 + \beta_1 A_i + \beta_2 L_i + \epsilon_i \\
\epsilon_i &\sim N(0, \sigma) \\
L_i|(S=1) &\sim TN(\mu_l, .25, 0, 1) \text{ assumed selection distribution} \\
\mu_l &\sim N(.9, .2) \text{ assumed selection distribution} \\
\beta_2 &\sim N(-4, 2) \text{ assumed load-voltage association}
\end{aligned}$$

Update using Bayesian inference with flat priors on β_o, β_1, and σ.

Sensitivity study results

Predicted voltage at 25 years comparing naïve analysis and sensitivity study.

- The pointwise median is in a darker color than the 95% pointwise confidence intervals.
- The true distribution lies within the 95% confidence intervals from the sensitivity study.
- Reliability estimate changes from .85 to 95% CI (.975, .993) under sensitivity study.



Conclusion

We present a simple example of how causal thinking can inform a reliability analysis.

- Advantages: informs how naïve analysis can be impacted by biases in data and what information to collect next, emphasizes the data generating mechanism.
- Limitations: very simple example, strong functional assumptions about relationships in the data, requires knowledge about the data generating mechanism that may not be available.

Conclusions: SCM gives a language for credibility of a prediction and may be useful in situations with ample *observational data*.

Future directions:

- Sensitivity studies can help determine what information to collect next – "value of information."
- Where else can causal methods improve data science in national defense and engineering?
  - Calibration and validation of computer models, where consideration of data generating mechanism and biases in data is critical.
  - Data fusion, when determining how to integrate multiple datasets with different information.

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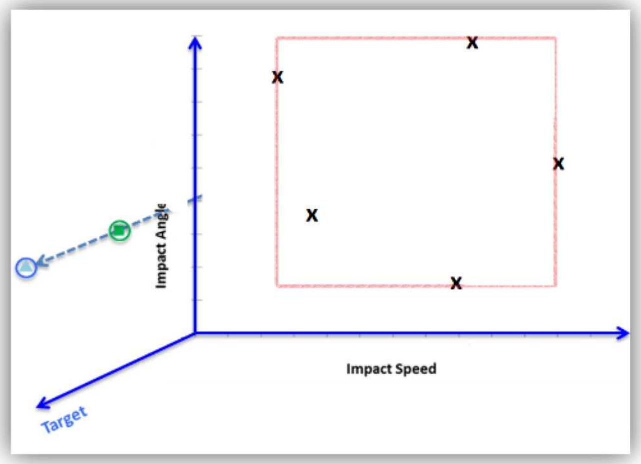
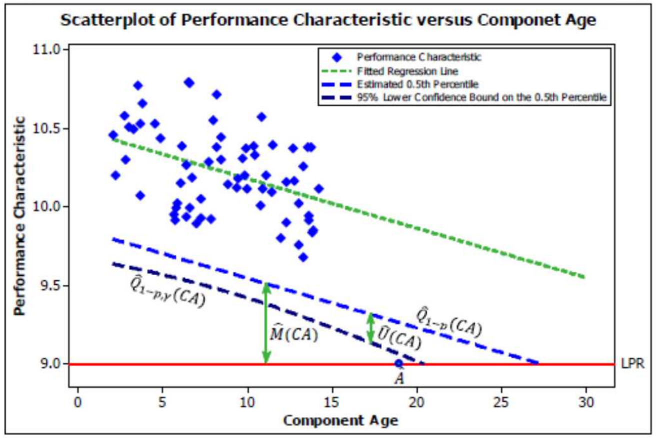
SCM in engineering applications

Limited work on causal inference methods in engineering applications:

- Need for causal inference methods in risk assessment (Aven 2014).
- Broniatowski and Tucker (2017) described high-level notions of validity that can be used to assess data-driven causal claims about engineering systems.
- Previous work has also considered how to learn causal networks in engineered systems from manufacturing data (Li & Shi 2007; Marazopoulou et al. 2016).
- We are concerned with reliability assurance applications where expert judgment is the primary source of information for building the causal network because data are biased and often sparse, which is a common situation in practice.





Value of information

Sensitivity study can inform what information to collect next.

- Value of information: consider cost relative to information gain.

$$VoI = E(C|\mathcal{D}) - E(C|\mathcal{D}, \mathcal{D}^*)$$

where C is cost, D is current information, and D* is new information to be collected.

- Consider "value of information" associated with:
  - Conducting more tests under current design.
  - Gathering more information about the load selection distribution.
  - Gathering more information about the load-voltage association.

Requires specifying cost structure on consequences of failing requirement.

- To avoid, can simply use statistical precision metrics.